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FRACTAL APPROACH TO THE REGIONAL SEISMIC EVENT DISCRIMINATION PROBLEM

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In the framework of the Comprehensive Test Ban Treaty, development of reliable methods to discriminate between underground nuclear explosions and earthquakes at regional distances (less than 2500km) continues to be very important especially in connection with the last (in May, 1998) nuclear explosions conducted at Indian and Pakistan test sites. Since the lithosphere is a fractal, we suppose the signals, which propagate through the media, inherit its 'self-similar' (scaling) features. We assumed that these features of explosions and earthquakes or their topological reconstructions (embeddings) have to be different. Scaling reflects correlations of more high order then it is possible to estimate by linear discriminating methods and can be used as base of non-linear discrimination. We propose to build a universal geometrical model of a seismic signal using the canon algorithm of F. Takens and to estimate scaling of the model. The scaling features were used as patterns of seismic signals for entering them into an artificial neural network. Records of nuclear explosions and earthquakes from different regions were included into the training set. The net was trained to classify types of seismic events. Results have shown 89% correct classification of the unknown signals. As additional tools for distinguishing between nuclear explosions and earthquakes we propose to use Hurst's method and the cross correlation method. Results of using these methods are demonstrated on examples of some explosions and earthquakes.

1 Introduction

The nuclear explosion discrimination problem continues to be very important especially in connection with the last (in May, 1998) nuclear explosions conducted at Indian and Pakistan test sites. Existing regional methods of seismic event discrimination [1,2,3,4,5] are based on the comparative analysis of spectral characteristics of two main components (P-wave and S-wave) of a seismogram (see Fig. 1). However, these parameters are very sensitive to non-uniformity of the lithosphere and the astenosphere and depend on the location of the event and the path of a signal propagation. Moreover, modern technology of nuclear testing complicates distinguishing between nuclear explosions and earthquakes.

It is known that the lithosphere exibites fractal features [6,7] in a wide range of

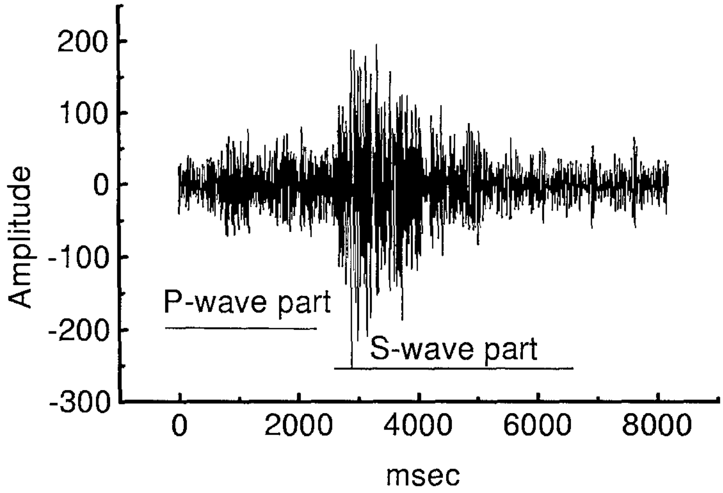

Figure 1. A seismogram of the Chinese earthquake, 24.07.86

scales - from parts of millimetre of geological grain to tens thousands kilometres of a tectonic plateau and has hierarchy of self-similar blocks. Response of the fractal lithosphere depends on source's geometry (radiation patterns) of a seismic event more than on its yields. Moreover, an earthquake centre is formed in the media during the long time. Features of the media are changed by the moment of the earthquake, which occurs in the preliminary stressed media. An explosion is an artifact for the media and is not connected with any preliminary changes of external parameters of the media. Since dynamic scenarios of explosions and earthquakes are different, we assumed that scaling features of seismic signals or their topological reconstructions (embeddings) have to be different. Scaling reflects correlations of higher order than it is possible to estimate by linear discriminating methods, and can be used as base of non-linear discrimination. We propose to build a universal geometrical model of a seismic signal using the canon Takens' algorithm [8,9] and to use its scaling features as attributes of seismic event discrimination.

The structure of this paper is as follows. In Sec. 2 we study 1D scaling features of seismograms. In Sec. 3 we study correlation dimension of reconstructions of explosions and earthquakes. In Sec. 4 we use the scaling features of embeddings of seismic signals as patterns for a neural network. In Sec. 5 we describe the cross correlation method as a tool for seismic discrimination. Our findings are summarized in the conclusion section.

2 Hurst's exponents of seismograms

We started from the study of self-similar properties of the processes in seismic sources applying Hurst's method [10] to the seismograms of nuclear explosions and earthquakes. Let us remind the classical notion of self-similarity for a random process[11]. $X(t)$ is a self-similar process in $\Re$ if there exists a sequence of positive real numbers c_r such that, for any $r > 0$,

$$X(t) \doteq c_r X(rt), t \in \Re \tag{1}$$

where $\doteq$ denotes equality of all finite-dimensional distribution. This equation is a statement of invariance of $X(t)$ under the group of affine transformations $X \to c_r X, t \to rt, c_r > 0$. Since $c_{a,b} = c_a c_b$ and $c_1 = 1$, c_r must have the form r^H for some $H > 0$ and this formula might be modified as

$$X(t) = r^{-H} X(rt), t \in \Re \tag{2}$$

where H is the Hurst exponent. Traditionally it is estimated by the rescaled range method [10].

We analyzed seismograms of the nuclear explosions conducted in India and Pakistan and Tibetian earthquakes. Fig. 2 represents the Hurst's exponents for different types of seismic events. Analysis of the Hurst's exponents allowed to conclude that graphs of the earthquakes are more regular than graphs of the explosions because H estimated for earthquakes equals 1 on larger range of scales (i.e. $\log T \in [0, 1.5]$) than for explosions (i.e. $\log T \in [0, 1]$).

It is necessary to note that the procedure described above is suitable only for records with low level of noise.

3 Correlation integral as a tool for distinguishing between different seismic sources

The estimation of the correlation dimension [12] of attractors reconstructed directly from experimental time series is often used means of gaining information about the nature of the underlying dynamics. It is proposed that a scalar time series $y(t) = \{y_i\}, i = 1, 2, ..., N$ have been generated by a smooth dynamical system $\mathbf{x}(t + \tau) = \mathbf{f}_\tau(\mathbf{x}(t))$ defined on a manifold M with an attractor $A \in M$ such that $y_i = h(\mathbf{x}(i\tau))$ where $h : M \to \Re$ is Lipschiz function. Then the reconstruction

$$\begin{gathered} \mathbf{y}(i) = \{y_i, y_{i+1}, ..., y_{i+m-1}\} = \\ = \{h(\mathbf{x}(t)), h(\mathbf{x}(t-\tau)), h(\mathbf{x}(t-2\tau)), ..., h(\mathbf{x}(t-(m-1)\tau))\} \end{gathered} \tag{3}$$

defines a *delay-coordinate map* $\Lambda : M \to \Re^m$ and $A \to A_\Re$ is the reconstructed attractor. Takens' theorem [8,9] ensures that if $m > 2D$ where D is the box-counting dimension (or capacity) of A, then the map Λ is embedding, i.e. is one-to-one, and also an immersion with a precision upto assumption about prevalence [13].

For Takens' theorem to be valid, we need to assume that both the dynamics and the observations are autonomous (so that $\mathbf{f}$ and h depend on $\mathbf{x}$ only). Unfortunately,

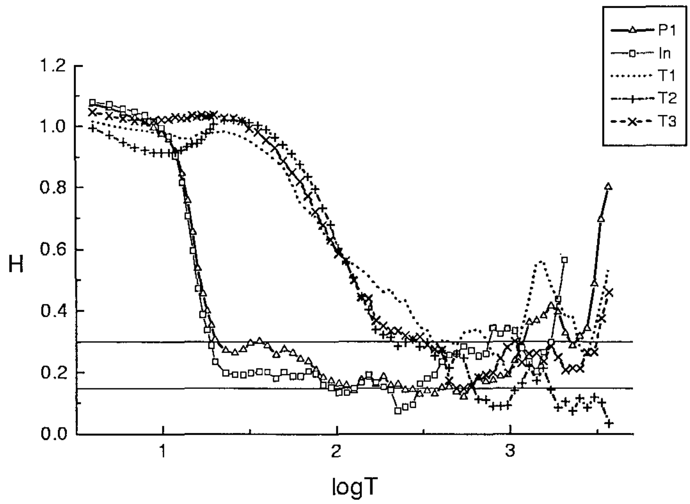

Figure 2. Hurst exponent H curves for different seismic events: Pak1 - nuclear explosion 30.05.98 (Pakistan), ind - nuclear explosion 11.05.98 (India), tib1 - earthquake (Tibet), tib2 - earthquake (Tibet), tib3 - earthquake (Tibet)

these assumptions fail to hold for seismic sources. However, there exists Takens embedding theorem for forced and stochastic systems [14]. We applied the technique of reconstruction described above basing on the last theorem and assuming that the seismograms are typical and contain all the character scales of the dynamics of the seismic sources. It means that in some sense the attractor of the seismic source exists.

We reconstructed some old non-camouflaged nuclear explosions and found out that their embeddings in $\Re^2$ visually differ from ones of earthquakes (see Figures 3-4). Unfortunately, this difference for records of last explosions (Indian and Pakistani explosions) is not visible (see, for example, Fig. 5). Therefore, it is reasonable to use numerous characteristics of these reconstructions. The most popular tool for description of the embedding obtained is the correlation integral [12].

Let $\mathbf{y}(i) \in \Re^m$ be a point on the attractor $A_{\Re}$. The correlation integral is defined as proportion of pairs of points of no more than distance ε apart. That is,

$$C_m(\varepsilon) = \frac{2}{N(N-1)} \sum_j \sum_k \Theta(\|\mathbf{y}(j) - \mathbf{y}(k)\| - \varepsilon) \tag{4}$$

Here: Θ - Heaviside step function, the symbol $\| * \|$ always denotes 'sup' norm on $\Re^m$.

There is scaling:

$$C_m(\varepsilon) \propto \varepsilon^{\nu} \tag{5}$$

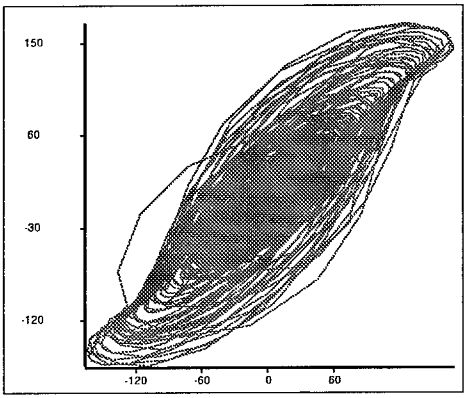

Figure 3. Embedding in $\Re^2$, nuclear explosion, STS, 25.04.82.

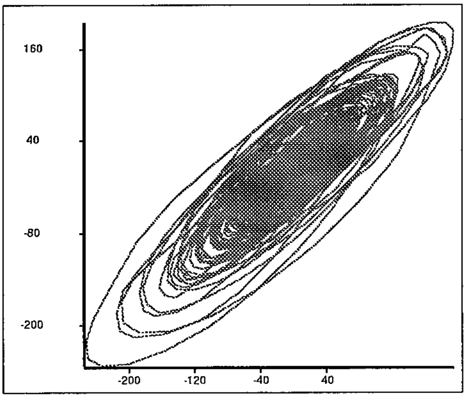

Figure 4. Embedding in $\Re^2$, earthquake, China, 24.06.86.

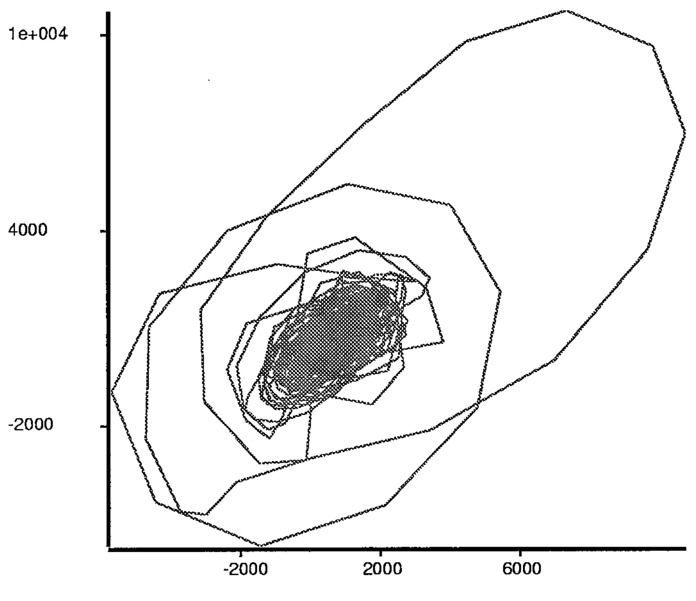

Figure 5. Embedding in $\Re^2$, the Indian nuclear explosion, recorded by NIL station, 30.05.98.

for $\varepsilon \longrightarrow 0$. The slope of the correlation integral is called *correlation dimension*

$$\nu = \lim_{\varepsilon \to 0} \frac{\Delta \log\ C(\varepsilon)}{\Delta \log \varepsilon} \tag{6}$$

The estimated ν typically increases with m and reaches a plateau (in the best case), on which the ν estimate becomes relative constant.

It is expected that because of the spherical symmetry and small sizes of sources

of underground explosions the main part of seismic energy is contained in compressional P-waves having high frequency content in comparison with earthquakes. At the same time earthquakes differ by generating intensive shear S-waves. These differences are traditionally used for choosing diagnostic parameters for seismic event discrimination. Hence, we studied the signals for both types of waves separately.

We processed records of underground nuclear explosions conducted at Semipalatinsk Test Site (STS,Kazakhstan) and Lop Nor (China) and earthquakes in China and Altay (Russia). The seismograms were recorded by Kazakhstani seismic stations BRVK, VOS, ZRN, CHK located in the North-West and TLG - in the South of Kazakhstan. In addition, seimograms of NIL station (Pakistan) were processed.

Our experience showed that correlation integrals for P-wave reconstructions are more informative than ones for S-waves: analyzing correlation integrals for S-waves we didn't find out notable features discriminating different seismic sources. Fig. 7 shows the typical correlation integrals for P-waves of nuclear explosions and earthquakes. It is seen that the correlation dimensions calculated for different types of seismic events are different. As a rule, the correlation dimensions are higher for explosions than for earthquakes.

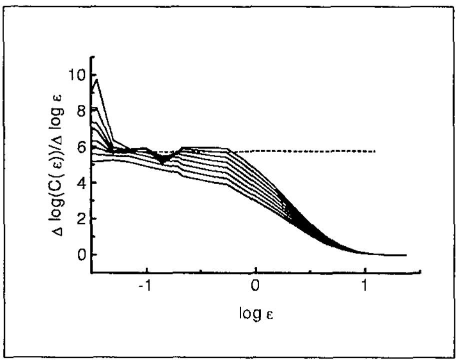

Figure 6. Slopes of correlation integrals ($m = 8-16$, $\tau = 2$), P-wave of the nuclear explosion, Semipalatinsk Test Site, 25.04.82.

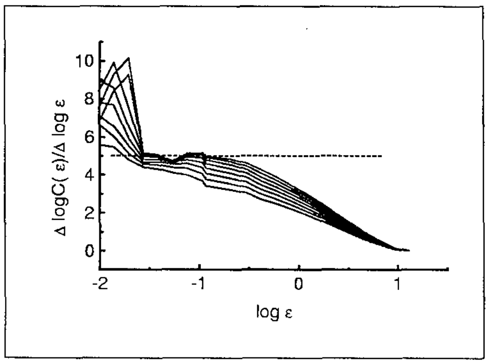

Figure 7. Slopes of correlation integrals ($m = 7-14$, $\tau = 2$), P-wave of the Chinese earthquake, 24.07.86.

In general case the slopes exibit complex behavior of ν versus ε Fig. 8. For complex systems it is possible that more than one scaling exists for different ε. The complexity of seismic record slopes might be explained by presence of different kinds folding effects in $\Re^m$ [17]. For the reasons outlined above we used the slope's form instead of the value of the correlation dimension, i.e. the function $\nu = \nu(\log \varepsilon)$.

We used this function, as discriminating attribute of seismic signals for training an artificial neural network to classify seismic sources.

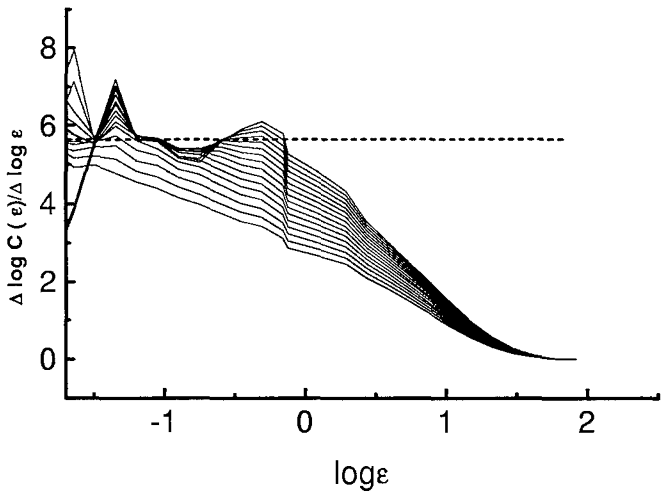

Figure 8. Slopes of correlation integrals ($m = 10-25$, $\tau = 2$), P-wave of the Indian nuclear explosion recorded by NIL station 30.05.98.

4 Neural network using

In the last decade artificial neural networks (ANN) have become the most popular tool for pattern recognition tasks [19,20] in general, and in seismic sources distinguishing in particular [3,4,5]. One can consider a neural network as a distributed dynamical system consisting of a set of non-linear processing elements (formal neurons) connected according to a certain architecture. The formal neuron is able to pick up input vectors $\mathbf{x} = \{x_j\}, j = 1, 2, ..., N$, estimate their scalar multiplications with weights $\mathbf{w} = \{w_i\}, i = 1, 2, ..., M$:

$$S = \sum_{i,j} x_j w_i \tag{7}$$

and transform S in accordance with an activation function ϕ into the output vector of the neuron $y = \phi(S)$. Such a neural network might be trained to recognize unknown patterns. Network training process is based on adjusting the weight connections between related values of inputs and targets (desirable outputs) so as to minimize an error function [19]. A set of input-targets values is called a *training* one. There exist two main types of ANN: fully-connected nets and perceptrons [20].

In order to check the algorithm described in the previous section we trained the fully-connected artificial neural network "MultiNeuron" developed by Russian scientists [20] using 60 examples of the correlation integral slopes of seismic records mentioned above as input patterns. The net was tested on 10 seismograms of different underground nuclear explosions and earthquakes which were not included

into the training set. Results of testing showed 89% of the correct classification of the signals.

5 Cross-correlation sums as a tool for distinguishing between different seismic sources

In this section we represent results of our study of non-linear cross correlation sums, which are the generalized correlation integrals and are used here for estimating similarity of two probabilistic measures.

Let $\{y_i\}$, $\{z_i\}, i = 1, 2, ..., N$ denote two different observed time series. Internal dynamics of systems in a phase space M which produces these series as typical mapping $M \rightarrow \Re$ is unknown. However, it is proposed that there exist chaotic or quasiperiodic attractors of these systems, dimensions of which d_y and d_z are low enough for applying the reconstruction's methods.

Let $A^{\mathbf{y}}_{\Re}$ and $A^{\mathbf{z}}_{\Re}$ be their embeddings into $\Re^n, n \geq 2(d_y + d_z)$. Let $\mathbf{y}$ and $\mathbf{z}$ be corresponding delay-vectors selected randomly according to two different measures μ and ρ. The cross correlation integrals are defined by[15] :

$$C_{\mu\rho}(\varepsilon) = \int d\mu(\mathbf{y}) \int d\rho(\mathbf{z})\Theta(\varepsilon - \|\mathbf{y} - \mathbf{z}\|) \tag{8}$$

The cross correlation sum is defined similarly by

$$C_{\mathbf{yz}}(\varepsilon) = N^{-2} \sum_{\mathbf{y}} \sum_{\mathbf{z}} \Theta(\varepsilon - \|\mathbf{y} - \mathbf{z}\|) \tag{9}$$

Almost surely, $C_{\mathbf{yz}}(\varepsilon) \rightarrow C_{\mu\rho}(\varepsilon)$ for $N \rightarrow \infty$, and $C_{\mathbf{yz}}(\varepsilon)$ is an unbiased estimator of $C_{\mu\rho}(\varepsilon)$. For sufficiently small ε and for absolutely continues measures μ and ρ one can show [15]

$$C^2_{\mu\rho}(\varepsilon) \leq C_{\mu\mu}(\varepsilon) C_{\rho\rho}(\varepsilon) \tag{10}$$

In practice, this inequality is used to calculate the cross correlation ratio as a similarity measure

$$r(\epsilon) = \frac{C_{\mathbf{yz}}(\varepsilon)}{\sqrt{C_{\mathbf{yy}}(\varepsilon) C_{\mathbf{zz}}(\varepsilon)}} \tag{11}$$

We used it in the form [16]

$$K^m_{\mathbf{yz}}(\varepsilon) = \sqrt{\frac{\sum_{i \neq j} \|\mathbf{z}(i) - \mathbf{z}(j)\|^2 \Theta(\varepsilon - \|\mathbf{y}(i) - \mathbf{y}(j)\|)}{\sum_{i \neq j} \Theta(\varepsilon - \|\mathbf{y}(i) - \mathbf{y}(j)\|)}} \tag{12}$$

If $\{y_i\}$ and $\{z_i\}$ are related by identical dynamical scenarios than one can expect that $\|\mathbf{y}(i) - \mathbf{y}(j)\| < \varepsilon \Rightarrow \|\mathbf{z}(i) - \mathbf{z}(j)\| \approx \varepsilon$. If no, $\|\mathbf{z}(i) - \mathbf{z}(j)\| \approx \Delta\mathbf{z}$, where $\Delta\mathbf{z}$ is the average distance between points of the attractor $A^{\mathbf{z}}_{\Re}$ and $K^m_{\mathbf{yz}}$ does not depend on ε.

Fig. 9 represents the cross corelations of various seismic events. The cross correlation between the Tibetian earthquake (09.01.90) and the Indian nuclear explosion (11.05.98) is absent: $K^m_{\mathbf{yz}}(\varepsilon)$ curve is practically in parallel with the horizontal axis.

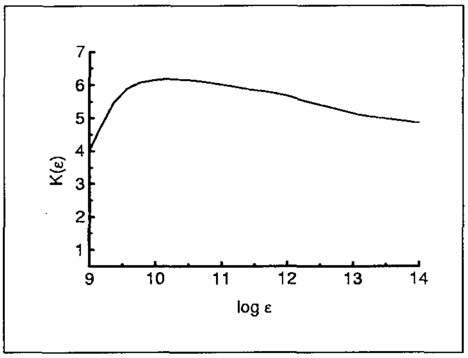

Figure 9. Cross correlation between reconstructions of the Tibetan earthquake and the Indian nuclear explosion.

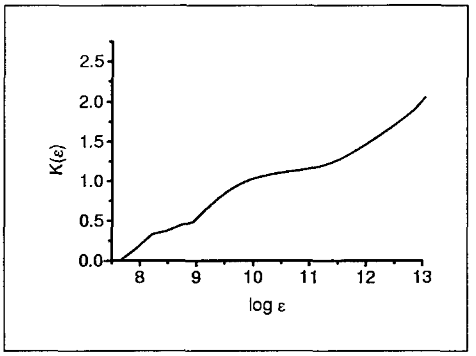

Figure 10. Cross correlation between reconstructions of the Indian and the Pakistani nuclear explosions.

The Figure 10 demonstrates strong cross correlation between the Indian explosion (11.05.98) and the Pakistani nuclear explosion (28.05.98). In this case we can conclude that dynamical scenarios of two systems observed are identical ones.

6 Conclusion

We have introduced non-linear criteria for distinguishing between underground nuclear explosions and earthquakes recorded at regional distances using the fractal approach.

We noted that behavior of Hurt's exponents varies for graphs of different seismograms in dependence on scale: the regularity range for the earthquakes is larger than for the explosions.

We found out that embeddings of non-camouflaged explosions into $\Re^2$ visually differ from ones of earthquakes. The slopes of correlation integrals demonstrate complexity of scaling. The notable plateau is absent for both types of seismic sources but the curves of the slopes are different for explosions and earthquakes.

The correlation dimension curves of 60 seismograms of different seismic events were entered into the neuroimitator "MultiNeuron", which was used as a classificator of underground nuclear explosions and earthquakes. The testing results obtained have shown 89% correct classification of 10 seismic events, which were not included into the training set.

Sometimes, it is possible to identify the seismic source estimating its cross correlation with a test example. Analysis of relationships of attractors in the phase space allows obtaining additional information for the discrimination task.

Therefore, our experience has shown that the non-linear methods could be successfully applied to regional seismic event discrimination.

Acknowledgments

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